Adoption of Big Data analytics tools by accountants practicing in South Africa

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ABSTRACT

This quantitative research paper investigates what drives accountants practicing in South Africa towards adoption of Big Data Analytics (BDA)tools. The study applies the unified theory of acceptance and use 2 (UTAUT2) model with an added construct namely, perceived threat of professional threat of obsolescence. 57 responds were deemed usable and analysed using SmartPLS and SPSS. Results from the sample suggest that the influence of effort expectancy on behavioural intention (BI) is stronger for younger accountants; social influence on BI is stronger for males; facilitating conditions on BI is stronger for the older group and hedonic motivation on BI is stronger for older males. Unmoderated results show social influence and hedonic motivation as key drivers towards adoptions. The findings of this study contribute theoretically by adding to body of work available on the subject of adoption of BDA tool by SA accountants; and practically by highlighting the importance of developing tools that pleasurable to us.

DECLARATION

I declare that this is my own unaided work and is, to the best of my knowledge and belief, original, except as acknowledged in the text.

I have read and understood the Senate policy on plagiarism and am aware that plagiarism is the intentional or unintentional "failure to acknowledge the ideas or writing of another" or "presentation of the ideas or writing of another as one's own". In this context, "others" means any other person including a student, academic, professional, published author or other resource such as the Internet. Failing to acknowledge the use of the ideas of others constitutes an important breach of the values and conventions of the academic enterprise.

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I have appended a reference list of citations used in this dissertation.

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Bongiwe Sellinah Sithole

Signed this ____16th_____ day of ___November___________________2023 in Johannesburg.

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Contents

1 INTRODUCTION

1.1 Background

Accountancy skills set are extensively reported as some of those that are under threat of being made obsolete due to advances in information technology tools. The World Economic Forum (WEF) Jobs report of 2018 and 2020 are some of the publications that have reported on this state of affairs. The 2022 WEF Jobs report had a dissimilar focus compared to preceding reports, it was centred around COVID 19 pandemic recovery jobs. The divergence from traditional accountancy comes as the profession seeks to cater to fast-changing requests of business, which cannot be adequately supported by the traditional tooling-person combination. Despite reports of technology disrupting the profession and possibly making it obsolete, adoption of new-age accounting technology remains slow (The Practice of Now 2020 report – Sage, 2020). “The rapid pace of technological innovations, including data analytics” has a great impact on the job performed by accountants (AICPA ,2020, p. 2).

The majority of literature available about new-age technology adoption is silent on accountants in South Africa. This inspired the curiosity of the author to seek to understand whether the phenomenon of slow adoption of big data analytics tools seen in developed markets applies to a developing market like South Africa (Agrawal, 2015; Lutfi et al., 2022), will the attitude of South Africans be found to replicate that observed in developed markets.

For this paper, the definition of accountant includes registered auditors. To be eligible for Registered Auditor (RA) status in South Africa, the Independent Regulatory Body of Auditors (IRBA) mandates one to hold a bachelors accounting degree or equivalent; honours degree in accountancy or equivalent and be a professional accountant (Chartered Accountant South Africa – CA(SA)). Thus, it can be said that all IRBA RAs are accountants. The definition of an accountant will also include affiliates of the South African Institute of Chartered Accountant (SAICA), certified professionals according to the Association of Chartered Certified Accountants (ACCA); Chartered Institute of Management Accountants (CIMA); and other uncertified accountants working in financial accounting and management accounting work streams.

Literature review shows Artificial Intelligence (AI), Cloud Accounting and Big Data Analytics (BDA), as some of the main technologies that are and will continue to have a considerable influence for accounting professionals (Moll and Yigitbasioglu, 2019; Richardson and Watson, 2021). The focus of this study is only BDA as it appears to be the technology whose rising demand is to the detriment of accountants (WEF Future of Jobs 2020; Schmidt and Riley, 2020).

Big data (BD) is described as hefty data volumes that may be structured and/or unstructured and proves traditional methods of analysis insufficient (Dewu and Barghathi, 2019). Seven constructs explicitly, velocity, volume, value, veracity, variety, valence, and variability are the foundation of BD (Saggi and Jain, 2018). The term BDA is used to combine Data Analytics and Big Data, while Najafabadi et al. (2015) and Salijeni et al., (2019) link BDA to mining and extricating meaningful patterns from large-volume data input for purposes of making predictions, decisions and drawing inferences.

Though Qasim and Kharbat, (2019) touch on big data, they centre their paper around Business Data Analytics. They are also silent on whether the business analysis term which they defined "The use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models [helps] managers gain improved insight about their operations, and make better, fact-based decisions" (Qasim and Kharbat, 2019, p. 109) is in any way connected to big data analytics which is the subject of the paper. According to these authors, slow adoption, and difficulty in implementing technology in the accounting field starts at the level of the undergraduate study where the curriculum has historically been resistant to accommodating technology that is used in industry. The same paper refers to a "rapid" (Qasim and Kharbat, 2019, p. 115) response from the accounting profession which is not being replicated in academia. The use of the word "rapid" is perhaps relative since other literature do not echo the same.

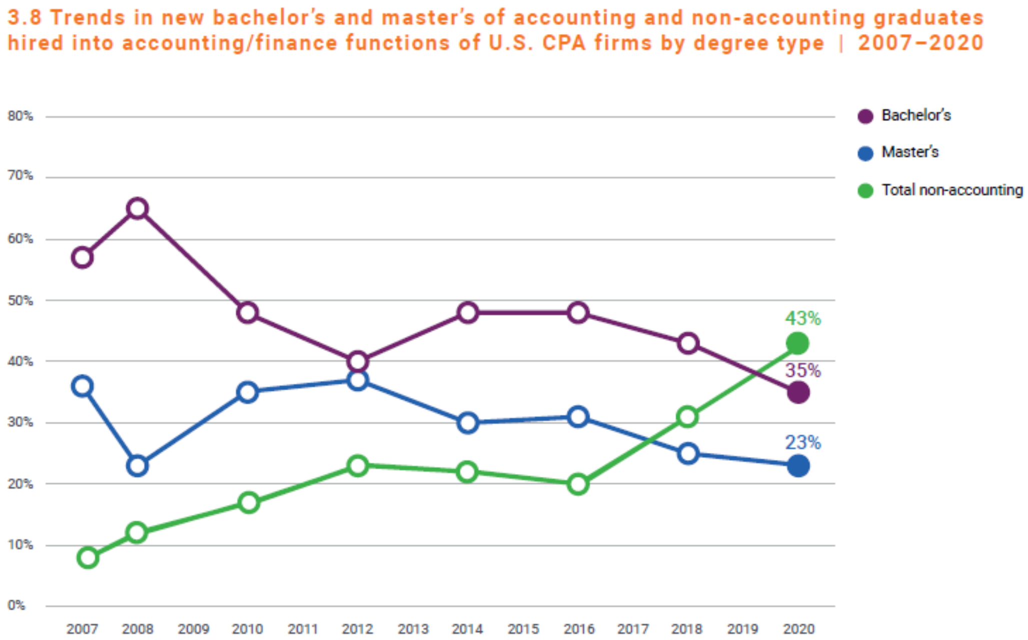
Accountants are well accustomed to structured data which usually comes from the company Enterprise Resource Planning (ERP) or other accounting software (Richins et al., 2017; Perkhofer et al., 2019). Big data introduces unstructured characteristics of the data which now play a big role in bringing about insights that the business requires. Herein lies the conflict, business requires the capability, and accountants may not have the tools or skill to meet the need – basic use of the Excel application may not suffice. The accounting profession enjoys the reputation of being slow to adapt and allow for new technologies to impact their world (Alles, 2015; Cordos and Tiron-Tudor, 2023), this however doesn't stop business and solutions from evolving. What has been observed regarding big data plus the analysis thereof is business simply sourcing those skills and competencies from other professions for instance data scientists (Schmidt and Riley, 2020). In Richins et al. (2017), it is suggested that audit firms face a possible threat of technology companies who are already driving techology innovation, entering the audit market. Examples of big data analytics tools relevant for accountants include Qlik Sense, Microsoft Power BI, SAP BusinessObjects BI Suite and Tableau Desktop (as per Gartner Analytics and Business Intelligence Platforms Reviews and Ratings for Europe, Middle East and Africa (confirmed in August 2022)).

1.2 Problem statement

Studies centred on accountancy and new technologies have been highlighting slow adoption of BDA tools as a key issue (Schmidt and Riley, 2020). In the Sage (2020) report it was documented that 69% of the respondents believed adoption could be quicker. Leaders of business are concerned about accountants possessing key big data analytics capabilities (Appelbaum et al., 2021). A study by AICPA (2019) showed evidence of a drop in employment of accountancy bachelor’s and master’s degree graduates, the jobs being lost to non-accounting professionals. Figure 1 depicts the rise in employment of non-accounting professionals taking up traditional accounting roles AICPA (2020). A link has been made in literature between adoption of BDA tools and the future of the accountancy profession being under threat (Richardson and Watson, 2021).

Despite concerns about obsolescence, adoption is still reported as low (Schmidt and Riley, 2020). The perceived threat of professional obsolescence has not been studied as a factor of the observed slow adoption. Professional obsolescence is the extent to which a professional feels threatened that their lack of current knowledge or necessary skills will render them unable to maintain an effective level of performance in either their current or future role as a result of advances in big data analytics tools (Kaufman, 1974; Joseph and Ang, 2001; Zhang et al., 2012; Singh and Kumar, 2019). Majority of existing relevant literature has investigated developed markets to the exclusion of developing markets (Agrawal, 2015; Lutfi et al., 2022) such as South Africa. This research will close the gaps by investigating professional obsolescence and the context of South Africa where adoption of BDA tools is concerned.

Figure 1: Accounting bachelor's vs accounting master's vs non-accounting degrees



Source: AICPA (2020, p. 38)

1.3 Purpose statement

The purpose of this research paper is to investigate factors that drive accountants practicing in South Africa to adopt big data analytics tools.

1.4 Research question

In order to understand what drives accountants in South Africa to make decisions around big data analytics tools adoption and thus the main research question:

What factors are driving accountants practicing in South Africa to adopt big data analytics tools?

To answer the main RQ, the following sub-research questions have been formulated:

RQ1: How do the attitudes of accountants differ from accountants studied in developed markets in regard to the adoption of big data analytics tools?

RQ2: Are there similarities to suggest generalisability of findings resulting from developed markets in regard to adoption of big data analytics tools?

1.5 Intended contribution of the study

1.5.1 Theoretical contributions

- The theoretical contribution of this research will be the investigation of perceived threat of professional obsolescence as a construct of adoption in the context of SA accountants.
- Literature on this subject is limited, this study will contribute towards closing that gap by bringing in a South African perspective.

1.5.2 Practical contribution

- This research will impact practice by pointing managers, professional bodies, and other leaders to focus their effort to boost adoption of big data analytics tools in order to better support business, safeguard the future relevance of the profession and aid accountants to avoid being made obsolete by DBA tools and practitioners of other professions.
- This research will also have an impact on the education of accountants at tertiary level. It will direct those who set the relevant curricula to make the necessary amendments so that they can produce graduates that are future-fit to cater to business demands.
- The study will highlight big data analytics tools adoption issues that are specific to South African accountants and provide opportunity to have these issues addressed as far as business is able to boost adoption.

1.5.3 Policy contribution

- Influence continuous professional development policies that are set by professional bodies such as SAICA and ACCA to include some level of proficiency in BDA tools to the list of required competencies for their members.

1.6 Delimitations of the study

This study will cover:

- Accountants which, will include registered auditors, CA's (SA), ACCA, CIMA and other uncertified accountants working in management accounting and financial accounting departments.
- Accountants practicing in South Africa so as to reduce the gap in available literature.
- Adoption of BDA tools will be the key technology investigated due to its rise in the rankings of a key skills for future jobs (WEF, 2020).

2 LITERATURE REVIEW

The purpose of this section is to explore how accountants interact with big data and to consider key findings from studies of a similar kind. Next, the threat of professional obsolescence is reviewed, followed by the concept of a hybrid accountant and finally, South Africa is reviewed as a context for the study.

2.1 Accountants and big data

Accountants can fall into three categories namely, management accountants (accountants that design measurement systems for performance and planning, utilising both nonfinancial and financial informational inputs, support organisations in the development and implementation of their set strategy (Atkinson et al., 2011;Uyar, 2021)), financial accountants (deal with the analysis of financial statements and other related data as a contribution to the strategy-fuelled process of making business decisions (Richins et al., 2017; Moll and Yigitbasioglu, 2019)) and auditors (audit the accounting procedures, accounting systems and the financial statements of a company, assess risk and perform financial management thereof (Independent Regulatory Body of Auditors, 2022)). Management accountants application of big data analytics would include utilising consumer sentiment data (about products and services) from social media to inform decisions around pricing; auditor application would include analysing customer tweets to determine whether warranty reserves are adequate for possible product recalls; financial accountants would use textual and numeric data to unveil that customer-base concentration has a negative relation with gross margin but a positive one with net profit (Patatoukas, 2012; Richins et al., 2017; Moll and Yigitbasioglu, 2019).

2.2 Findings from similar studies

The Riley et al. (2020) study focused on the resistance to change which was observed from accountancy professionals. These authors found that accountants were likely to resist shifting to big data analytics tools that are more sophisticated despite being knowledgeable of the benefits if they deemed switching costs too high. There are three elements to switching costs namely, sunk costs (past investments to current technology (Schmidt and Riley, 2020)), uncertainty costs (the avoidance of feeling inadequately skilled (Brown and Venkatesh, 2015;

Schmidt and Riley, 2020)), and transition costs (when one resists change to evade losses (Kahneman and Tversky, 1979; Schmidt and Riley, 2020)). Perceived value (which encompasses the net of switching costs and benefits (Kahneman and Tversky, 1979; Rauramo, 2021)) is comparable to perceived usefulness (defined as the extent to which one is of the view that using a particular technology can improve their job in some way) according to the Technology Acceptance Model 3 (Venkatesh and Bala, 2008). Schmidt and Riley's (2020) study as well as Venkatesh and Bala's (2008) study have both found evidence to support the position that one's perception of a tool's ability to provide value can act as a motivating factor towards adoption. According to Venkatesh and Bala's (2008) Technology Acceptance Model 3, perceived usefulness ranked as one of the strongest drivers towards technology adoption among individuals.

Perkhofer et al. (2019) found that though in early stages, some level of big data visualisation adoption has been observed in Austrian management accountants. Similar to Schmidt and Riley (2020), the "sole focus on using Excel" (Perkhofer et al. 2019, p.515) was identified as a barrier to adoption. Other key findings by Perkhofer et al. (2019) include that using multiple data sources increases use of visualisation tools; and being unfamiliar with and lacking knowledge of new and interactive visualization options hinder adoption.

Data quality challenges (especially the unstructured data), investment in technology (software and hardware), a shortage of auditors who are skilled in data science, and implementation costs (such as training costs) will be barriers to adoption (O'Donnell and Sauer, 2018).

Rickett (2017) suggests some barriers to adoption, namely: education and training of accountants; technology adoption, behaviour implications; and lack of data centric audit standards. Similar barriers are reported in Keiper et al. (2023). An article published in Accountancy SA (2021) cited reasons for slow adoption as, denial that change is coming, the fact that accounting standards adapt at slower pace than technology, simply automating manual procedures without undergoing the required mind shift which often results in efficient processes. This article, though focused on South Africa was not a scholarly paper.

2.3 Threat of professional obsolescence

Individuals working in rapidly advancing fields are at risk of facing professional obsolescence (Pazy, 1990; Wiedenhoeft, 2022). Rapid technological advances and growing business complexity are posing significant challenges to the accountancy field. This is reflected in the

World Economic Forum's 2018 and 2020 jobs reports, which have ranked accountancy as the 7th and 4th profession, respectively, with an anticipated decline in demand. The definition of obsolescence is subjective to the individual (Pazy, 1994; Gussek et al., 2021). Nevertheless, Joseph et al. (2007) have adopted the Joseph and Ang (2001) definition in which perceived threat of professional obsolescence is defined to be the level of threat experienced by one because of continuous technology advances. The Joseph and Ang (2001) definition adds the component of technology, though short of specificity regarding by whom the fear is experienced as well as the context thereof. The release of new technology can cause individuals to feel threatened in their personal capacity, but this may not necessarily be said to be the threat of professional obsolescence. Threat of professional obsolescence (TPO) is the level to which one lacks proficiency compared to their professional peers concerning methods, knowledge, and crucial technology (Shearer and Steger, 1975; Hösch et al., 2023). This definition is challenging given it solely touches on individuals compared to peers in their respective fields. According to the Kaufman (1974) definition, TPO is the extent to which a professional is deficient of current skills/knowledge that are essential in enabling them to uphold an effective performance level in their current role or future aspirational roles (Zhang et al., 2012; Singh and Kumar, 2019).

Findings from Zhang et al. (2012) suggest that perceived obsolescence has an age moderated adverse influence on embeddedness. This finding stems from a study that specifically targeted Information Technology professionals, a group widely acknowledged and extensively documented in academic literature as the primary beneficiaries of technological disruption. Therefore, it is sensible that this construct be considered in the proposed model. In terms of this paper, perceived threat of professional obsolescence will be defined as the level of concern experienced by a professional regarding their lack of current knowledge or necessary skills will render them unable to uphold an effect standard of professional performance in either their current or future role as a result of BDA tool advancements (Kaufman, 1974; Joseph and Ang, 2001; Zhang et al., 2012; Singh and Kumar, 2019).

Richins et al., (2017) highlight that the threat of complete automation of the audit and accounting function is complex. In unpacking this complexity, they present two types of analysis for the two data types (structured and unstructured): problem driven and exploratory. They then suggest that there is room for both accountants and data scientists to add value. These authors are highlighting the fact that exploratory analysis of data is highly technical, and the accountants can add value in the analysis and interpretation rather than the mining of data;

while problem driven analysis require someone with "domain specific knowledge" (Richins et al., 2017, p. 19) which would be accountants in this context. This suggests that perhaps accountants do not need to be fully-fledged data scientists – that, some level of competence in data is required but complex exploratory data mining can be rightfully outsourced to a data scientist. "The work of an accountant will need to go beyond bookkeeping and reporting towards activities that require interpretation, judgement or evaluation" (Jędrzejka, 2019, p.156).

2.4 Hybrid Accountant and other considerations

Gamage (2016) emphasized the concept of a hybrid professional who possesses both financial and technological competencies. The idea of a hybrid professional (finance, information and technology) is further emphasized in Fettry et al. (2019). Including technology as a component of the proposed hybrid prompts considerations relating to computer anxiety and computer self-efficacy (one's perceptions regarding their competence in using a particular technology) (Venkatesh and Bala, 2008). Experience and confidence influence adoption of big data analytics tools (Salijeni et al., 2019), a point of view echoed in Venkatesh and Bala (2008). Independence of the mind and appearance are key considerations where BDA tools adoption is considered for auditors (IRBA Code of Professional Conduct for Registered Auditors, 2018). Embracing big data analytics tools has the potential to cause issues of independence as lines between auditor and client get blurred through the process of adoption. This blurring stems from both parties sharing learnings and/or the audit firm also performing BDA tools advisory services (Salijeni et al., 2019). The likely impairment of independence could steer away from adoption. Issues of privacy, security, storage and processing are examples of Dewu and Barghathi's, (2019) Perception of External Control (the level to which one believes that their organisation possesses the adequate organisational and technical resources to support their technology usage). Thereby suggesting that accountants are more likely to move towards adoption of BDA tools if they deem their organisation as having reliable support to ensure data privacy, avail appropriate and secure data storage and efficient computer processing power.

It has been documented that the big data tools cater for structured data which accountants are already well accustomed to (Richins et al., 2017; Wadesango et al., 2021)) and in addition to that they bring about efficiencies and improved effectiveness through advanced analysis of data. This suggests that adoption of tools could be independent – accountants may not require advanced spreadsheet skills even as they transition or not transition to considering unstructured data in their analysis. Business has evolved from miniscule information to large volumes of data – even within the confines of structured data – it's "rows and columns on a spreadsheet without the right tools", making it difficult to find insights and meaning in the data (Richins et al., 2017, p. 11). Efficiencies and improved effectiveness include capability to test the full population of transactions instead of sampling which results in ease of data trends and patterns identification; support for continuous auditing; improved fraud detection and advanced pricing models (O'Donnell and Sauer, 2018).

2.5 South African context

South Africa is an emerging market that faces challenges which may not be relevant for the developed world (IMF, 2022). An example of this is the high rate of unemployment which sky-rocketed to 34.5% as a result of the novel corona virus (Stats SA, 2022). Since jobs are already scarce, it becomes pertinent to study and understand possible threats to an entire profession. Accountants have played a key role in the economy of South Africa and are well-received across the world (Accountancy SA, 2021). In other markets, some of the jobs have seemingly been lost to data scientists (Schmidt and Riley, 2020). The demand for data scientists is on the rise in South Africa and the country came in 6th place globally for hiring data scientists (BusinessTech, 2022). As stated, literature on adoption of BDA tools in South Africa is limited, findings from other studies focusing on adoption in Sub-Saharan Africa (SSA) will be considered. These include contributions by Danquah and Amankwah-Amoah (2017) who found that technology adoption increased marginally by 1.7% 1960 – 2010 for SSA (3.7% for South Africa). Another finding was that human capital which they defined as "knowledge and skills embodied in people and accumulated through schooling" (Danquah and Amankwah-Amoah 2017, p. 25), positively impacts adoption of technology. The findings are insightful; however, they were based on old data which may no longer be relevant.

3 THEORETICAL MODELS

3.1 Introduction

Various theoretical models have been proposed to understand the adoption of new technologies by individuals (Lai, 2017). This section will consider some of these theories for possible application for this research. Due to applications in previous similar studies, the following theories will be considered; Theory of Big Data Analysis for Auditing Adoption, Status Quo Bias Theory, Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) and Technology Acceptance Model.

3.2 Status Quo Bias

According to Schmidt and Riley, (2020), integrated Status Quo Bias (SQB) theory is a combination of SQB, Equity-Implementation Model and Theory of Planned Behaviour (Ajzen, 1991; Samuelson and Zeckhauser, 1988; Joshi, 1991). Integrated SQB theory aims to explain why one is driven towards maintaining things as they are (Schmidt and Riley, 2020). Unlike Schmidt and Riley (2020), this paper seeks to understand drivers towards adoption by accountants, SQB is therefore deemed unsuitable for the context of this paper.

3.3 Technology Acceptance Model 3

Perkhofer et al. (2019) studied adoption of interactive visualisation of big data in the Austrian market using the perceived ease of use (the degree to which one holds the view that an information technology (IT) will be effortless (Venkatesh and Bala, 2008)) – a construct from TAM3. The complete TAM3 model positions "individual differences, system characteristics, social influence, and facilitating conditions" (Lai, 2017, p. 28) as determining factors of perceived ease of use and perceived usefulness. There is limited research available on South Africa with regards to adoption of BDA tools by accountants, we would therefore be remiss to limit this study only to perceived ease of use.

3.4 Theory of Big Data Analysis for Auditing Adoption

To explore the adoption of big data analytics, O'Donnell and Sauer, (2018) developed the Theory of Big Data Analysis for Auditing Adoption (BDAAA) which effectively merges

Diffusion of Innovation Theory (DIT) and Technology Acceptance Model (TAM). This BDAAA is a new model and is yet to be extensively tested by other peers, furthermore, the model was designed for the context of audit rather than accountancy in general. Since this study focuses on auditors and other accountants who are not auditors, BDAAA will not be appropriate to apply.

3.5 Unified Theory of Acceptance and Use of Technology 2

UTAUT2 is considered to be the most comprehensive theoretical framework in studying adoption and use of technology at an individual level (Macedo, 2017; Tamilmani et al., 2019). UTAUT2 is a powerful theoretical model and a build up from TAM2 (Lai, 2017). This model considers multiple factors which improves it predictive power (M et al., 2021)This research will be the first of its kind, it is therefore prudent to make use of a model that is known for comprehensiveness. Applying UTAUT2 in various contexts is encouraged by Venkatesh et al. (2012). This research honours the call of applying UTAUT2 in a new context. BDA tools are new technology utilised by individual users and the South African context presents a different dynamic and setting, this further supports the decision to opt of UTAUT2 (M et al., 2021).

There are seven constructs in the original UTAUT2, namely, performance expectancy, hedonic motivation, effort expectancy, social influence, habit, facilitating conditions and price value. Performance expectancy refers to the extent to which using BDA tools provides benefits to accountants as they perform their duties, effort expectancy is defined as the extent of ease that is associated with accountants' use of BDA tools; social influence refers to the degree to which accountants believe that those who matter to them believe they should use BDA tools; and facilitating conditions refer to perceptions held by accountants regarding the availability of resources and availability of support to aid the utilisation of BDA tools (Venkatesh et al., 2003; Brown and Venkatesh, 2005; Sithole. 2022).

Nuances at the individual level namely: age, gender, voluntariness, and experience moderate of the relationships observed in UTAUT2 (Venkatesh et al., 2012). Perceived threat of professional obsolescence is a new extension of the original UTAUT2.

Contrary to Venkatesh et al. (2012) where the cost of the technology was for the account of the consumers, in the context of this paper, the cost will likely be covered by the employer organisation. For this reason, there is no price value in the research framework of this paper.

4 HYPOTHESES

Influence of performance expectancy on behavioural intention, with age and gender as moderators.

Behavioural intention tends to be significantly influenced by performance expectancy (Ain et al., 2016). Gender and age moderate the relationship between performance expectancy and behavioural intention (Venkatesh et al., 2012, 2003). With regards to awareness of how useful new technology is, young men tend to lead (Kwateng et al., 2019). Therefore, younger male accountants who perceive big data analytics tools as value adding are likely to want to adopt the tools. Value

H1: Age and gender will moderate the relationship between performance expectancy and behavioural intention to the extent that the influence will be positive in the case of younger male accountants.

Behavioural intention influenced by effort expectancy, with age, gender, and experience as moderators.

The impact of effort expectancy on behavioural intention as moderated by gender, age and experience is stronger for females that are older and have limited experience (Venkatesh et al., 2012, 2003). "If a user thinks that it is easy to use the technology for conducting an activity, then the user may have a higher acceptance for the new technology" (Singh and Matsui, 2017, p. 4). Simpler user experience leads to increased usage intentions (M et al., 2021). Hence, older female accountants with limited experience and view a big data analytics tool as easy to use are likely to want to adopt the tool.

H2: Age, gender and experience will moderate the relationship between effort expectancy and behavioural intention to the extent that the influence will be positive for older female accountants with limited experience.

Behavioural intention influenced by social influence, with gender, age, experience, and voluntariness as moderators.

The utilisation of new BDA tool by "socially connected" individuals could serve as perceived or explicit influence towards use intention (Singh and Matsui, 2017, p.5). The impact of social influence on behavioural intention as moderated by gender, age, experience and voluntariness is stronger for women that are older, have restricted experience and are subjected to mandatory use (Venkatesh et al., 2012, 2003). Therefore, older female accountants who have limited experience and are obligated to, are likely to want to adopt a big data analytics tool if they believe those they hold in high regard believe they should adopt.

H3: Age, gender, experience and voluntariness will moderate the relationship between social influence and behavioural intention to the extent that the influence will be positive in the case of older female accountants with limited experience and are subjected to obligatory use.

Behavioural intention influenced by facilitating conditions, with age and gender as moderators.

Facilitating conditions are said to be attributes of the organisation (Venkatesh et al., 2016). The impact of facilitating conditions on behavioural intention as moderated by age and gender is stronger for older women (Venkatesh et al., 2012). The elderly are likely to encounter challenges in coping with new technologies; men tend to be more driven to overcome challenges in order to achieve their goals (Venkatesh and Morris, 2000; Kwateng et al., 2019).

H4: Age and gender will moderate the relationship between facilitating conditions and behavioural intention to the extent that the influence will be positive for older female accountants.

Usage influenced by facilitating conditions, with age and experience as moderators.

The impact of facilitating conditions on usage as moderated by age and experience was found to be significant for those who are older and have limited experience (Venkatesh et al., 2003). Advance experience with technology tends to result in better user learning (Alba and Hutchinson, 1987; Kwateng et al., 2019).

H5: Age and experience will moderate the relationship between facilitating conditions and use to the extent that the influence will be positive in the case of older accountants with little experience.

Behavioural intention influenced by hedonic motivation, with age, gender and experience as moderators.

Intention to use can be influenced by hedonic motivation where users are entertained or excited by using a new, pioneering technology. The effect of hedonic motivations on behavioural intention as moderated by age, experience and gender is stronger for men who are younger and have limited experience (Venkatesh et al., 2012). Increase in experience leads to use for "purposes that are more pragmatic", while age and gender are linked to the innovativeness of the technology (Kwateng et al., 2019, p. 8).

H6: Age, gender and experience will moderate the relationship between hedonic motivation and behavioural intention to the extent that the influence will be positive in the case of younger male accountants with little experience.

Behavioural intention influenced by habit, with gender, age and experience as moderators.

The instinctive act of using technology is a component of habit and users who are in the habit of using technology will tend to do so as a reflex (Singh and Matsui, 2017). Habit is linked to automatic behaviour (Ferratt et al., 2018). The relationship between habit and behavioural intention as moderated by gender, experience and age is stronger for older males that are highly experienced with technology (Venkatesh et al., 2012).

H7: Age, gender and experience will moderate the relationship between habit and behavioural intention to the extent that the influence will be positive in the case of older male accountants with advanced experience.

Habit influenced by habit, with age, gender, and experience as moderators.

The influence of habit on usage as moderated by age, gender and experience is stronger for older males with high levels of experience (Venkatesh et al., 2012). According to Venkatesh et al., (2016) old habits may adversely affect new technology usage.

H8: Age, gender and experience will moderate the relationship between habit and usage to the extent that the influence will be stronger in the case of older male accountants with advanced experience.

Usage influence by behavioural intention, with experience as a moderator.

Demissie et al., (2021) suggest that behavioural intention encompass plans of use continuation and is connected to convictions about technology effectiveness rather that convictions about use a certain technology. The relationship between behavioural intention and usage as moderated by experience is stronger for those with less experience (Venkatesh et al., 2012).

H9: Experience will moderate the relationship between behavioural intention and use to the extent that the influence will be positive for the accountants with less experience.

Behavioural intention influenced by perceived threat of professional obsolesce, with age as a moderator.

Increased perceived skills obsolescence can be directly linked to technology innovation (Standridge and Autrey, 2001). Workers will counter the increase in perceived skills obsolescence by engaging in upskilling programmes (Harden et al., 2018). Older workers tend to have higher sunk costs in terms of being more experienced in older technologies (Zhang et al., 2012). It is therefore expected that the effect of perceived professional obsolescence on behavioural intention will be strong for younger accountants.

H10: Age will moderate the relationship between perceived threat of professional obsolesce and behavioural intention to the extent that the influence will be positive in the case of younger accountants.

According to Kwateng et al. (2019), youth is 30 years and below in age. Some professional accountant qualifications take up to 7 years to attain, for this reason this paper will consider younger accountants to be 35 years old and below, 36 and above will be regarded as older. Advanced/ higher levels of experience will be more than 3 years while little/ lower levels will be considered 3 years and below (Kwateng et al., 2019).

Hypotheses adapted from (Venkatesh et al., 2012, 2003)

Figure 2 highlights the nomological structure.

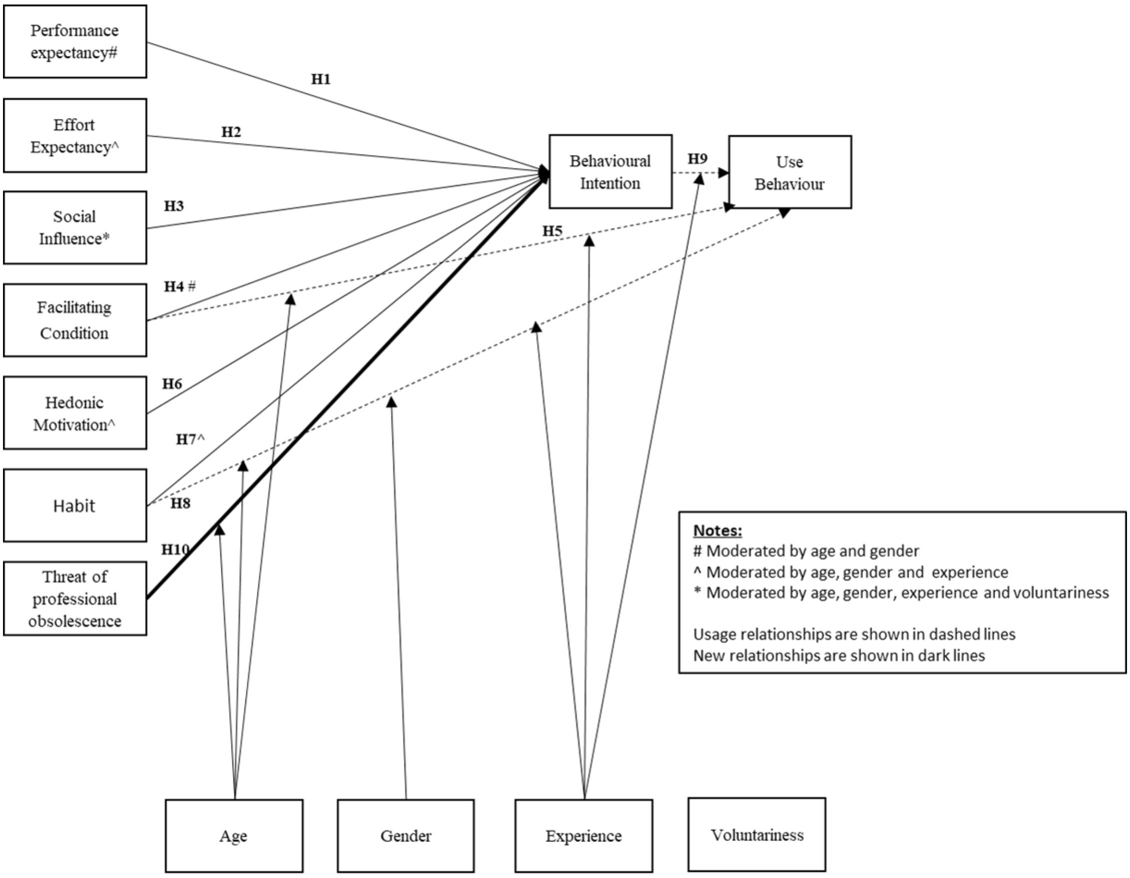


Figure 2: UTAUT2 (Modified)

5 RESEARCH METHODOLOGY

5.1 Research Paradigm and Approach

The phenomenon of technology adoption at an individual level has been widely studied with theories being developed by various scholars over the years. Examples of these theories are TPB, TAM, TAM2, TAM3, UTAUT, UTAUT2 (Ajzen, 1991; Venkatesh et al., 2003; Brown and Venkatesh, 2005; Venkatesh and Bala, 2008; Venkatesh et al., 2012). This study tests adoption using the existing theory of UTAUT2 on new empirical data, therefore the approach is deductive (Bhattacherjee, 2012).

Ontology refers to assumptions around how the world is and epistemology; is anchored in the ideal method of studying the world (Burrell and Morgan, 1979; Bhattacherjee, 2012). According to Orlikowski and Baroudi (1991), ontology looks at whether social and physical worlds are objective and exist independent of human beings versus being subjective and existing only through the actions undertaken by the same; epistemology on the other hand looks at criteria to apply to constructure and evaluate knowledge.

For this deductive research, the author believes they play a neutral and passive role in studying the adoption phenomenon; and that the insights into the problem of slow adoption amongst accountants will be unveiled through an established adoption model UTAUT2. This will verify or falsify the chosen model. Based on all this, this research paradigm is positivist. (Bhattacherjee, 2012)

5.2 Research Design and Strategy

Research design produces a roadmap of tasks that have to be completed in the pursuit of adequately answering the research question, it is comprised of three major steps: namely operationalising the relevant constructs, selecting a research method and sampling strategy (Bhattacherjee, 2012).

5.2.1 Operationalisations

As per UTAUT2 (Venkatesh et al., 2012), the relevant constructs are operationalised as follows:

- performance expectancy – the degree to which individuals believe their jobs will be made easier through using big data analytics,
- effort expectancy - the extent of ease that is ascribed to big data analytics tools,
- social influence – the extent to which one is of the view that those who matter to them want them to use big data analytics tools,
- facilitating conditions - environmental factors which are said to be objective and agreed upon by observers to bring about ease to using big data analytics tools.
- hedonic motivation – fun associated with using big data analytics tools,
- habit – “self-reported perception” (Venkatesh et al., 2012, p.162) about big data analytics tools.

5.2.2 Perceived threat of professional obsolescence

As a construct modified into UTAUT2, perceived threat of professional obsolescence is the extent of threat a professional experiences due to a lack of current knowledge or skills that are necessary to enable them to maintain an effective level of performance in either their current or future role as a result of advances in big data analytics tools (Kaufman, 1974; Joseph and Ang, 2001; Zhang et al., 2012). Modification of UTAUT2 can also be observed in Gansser and Reich, (2021) where safety security, personal innovativeness, sustainability, health and convenience comfort as constructs were added to UTAUT2. Perceived product advantage and perceived security were added to the UTAUT2 model by (Schmitz et al., 2022) to study telemedicine adoption.

Moderator of these relationships are age, gender, voluntariness, and experience - (Venkatesh et al., 2012, 2003).

5.2.3 Sampling strategy

“Sampling is a statistical process of selecting a subset (called a “sample”) of a population of interest for purposes of making observations and statistical inferences about that population” (Bhattacherjee, 2012, p. 65). Participants were primarily recruited in the finance department of a Fast-Moving Consumer Goods (FMCG) company operating in South Africa. The FMCG has more than 30 manufacturing plants across South Africa and manufactures basic foods, beverages and snack. The finance department is comprised of 620 employees. For this research the target sample is 238 respondents based on Raosoft sample calculator. The questionnaire was distributed to prospective participants via email.

5.2.4 Data Collection Methods

According to Bhattacherjee (2012) data collection methods can be grouped into two categories based on their philosophies: positivist and interpretive. Hypothesis-testing survey research and laboratory experiments are examples of positivist methods (deductive approach). The type of data used in positivist research is largely quantitative and can sometimes feature qualitative data. Interpretive methods include action research and builds a theory from data about the phenomenon of interest (an inductive approach). Interpretive research will use data that is largely qualitative and can sometimes feature the quantitative as well. Dubé and Paré (2003) suggested using various other methods to collect data and coupling quantitative with qualitative methods. This prevents researchers from being misled by readings from quantitative data, qualitative data can then corroborate or dispel inaccurate finding from the quantitative (Eisenhardt, 1989). In line with Venkatesh et al. (2012), this research makes use of a survey directed at the accountants (quantitative). Refer to appendix 11.1 for the research instrument. Ethical consideration were made and ethical clearance was obtained, refer to appendix 11.3.

With the exception of perceived threat of obsolescence, the scales of the constructs are aligned to those in Venkatesh et al. (2012) and Venkatesh et al. (2003) given this research is deductive. The seven-point Likert scale is used to measure the items, anchors range from “strongly agree” to “strongly disagree”. In the case of the “Use” constructs, a five -point Likert scale is used, anchors range from “never” to “multiple times a day”. For “use”, participants are presented with a list of four big data analytics tools (namely Power BI, Qlik Sense, SAP BusinessObjects BI Suite, Tableau Desktop) currently on the market and requested to indicate how frequently they use each of the tools. This study will be measuring age and experience in terms of years.

As it is the norm for quantitative studies, this study makes use of random sampling. Random sampling increases generalisability to the broader population and allows all participants equal probability to be selected. (Bhattacherjee, 2012; Creswell, 2017).

The survey was e shared with prospective participants with a target response rate of 50% (Fincham, 2008; Draugalis and Plaza, 2009).

Perceived threat of professional obsolescence scales will be aligned to Zhang et al. (2012). Consistent with other constructs in this research, items are measured using the seven-point Likert scale. Refer to appendix 11.1 for the research instrument.

5.3 Data Analysis Process

5.3.1 Reliability and validity testing

Reliability is the extent to which the measure of a construct is consistent or dependable – if the scale was to be used several times to measure the same construct, the result would be the same provided the phenomenon is also the same (Bhattacherjee, 2012). There are several methods of testing reliability of measures, such as Internal consistency reliability which measures consistency between multiple items of the same constructs (Bhattacherjee, 2012). Cronbach's alpha is a method commonly used by researchers to prove that tests and scales are suitable for purpose (Taber, 2018).To ensure the reliability of the scales, Cronbach's alpha was calculated for the items and accepted at 0.70 and above in line with common practice (Taber, 2018).The methods of testing reliability measures included Inter-rater reliability, which measures consistency between a minimum of independent raters observing the same construct; test-retest reliability measures consistency between two measurements of the same construct and sample but different time points (Bhattacherjee, 2012).

Validity refers to the degree to which a measurement accurately and adequately represents the intended construct it is meant to assess, rather than measuring something unrelated or different (Bhattacherjee, 2012). Convergent validity looks at how closely a measure relates to the construct that it is claimed to measure while discriminant validity refers degree to which a measure is not measuring other unrelated constructs that it shouldn't be measuring (Bhattacherjee, 2012).

5.3.2 Descriptive statistics

Descriptive statistics serve the purpose of organizing and summarizing data in a systematic way, enabling the depiction of the relationship between variables within a given sample or population (Ali and Bhaskar, 2016). Descriptive statistics play a crucial role in the initial analysis of data and form the basis for comparing variables using inferential statistical tests (Kaur et al., 2018). The mean and the standard deviation are calculated to ascertain the shape of the sample data and inform the best suited inference statistics. Omitting this step could result in incorrect interpretation of the inferential statistics(Mishra et al., 2019)

5.3.3 Inference statistics

SPSS software was used to compute the inferential statistics. The statistical test one selects is dependent on type and shape of the data as well as the nature of the research question (Creswell, 2017). Due to the complexity of the relationships, Venkatesh et al. (2012) used the partial least squares (PLS) method.

Questionnaire data was coded (conversion of data to numeric form (Bhattacherjee, 2012)) according to the five-point and seven-point Likert scales as explained in Section 4.2.3. It was entered onto an Excel spreadsheet allowing for easier reorganisation and identification of data that needed to be ignored in further analysis (Bhattacherjee, 2012). This study composed of the bivariate correlation to test the relationship between the variables as per the modified UTAUT 2 model, and then followed by the statistical testing of the strength thereof through hypotheses (Bhattacherjee, 2012). The null hypothesis – h0 denoting that there is no relationship, and the alternative hypothesis is represented by h1. Type I and Type II errors can occur in hypothesis testing. Type I is incorrect rejection of the null hypothesis while Type II is failure to reject a false hypothesis (Bhattacherjee, 2012; Dijkstra and Henseler, 2015). p-value equals was considered at the significance level of 10% (Kwateng et al., 2019).

6 RESULTS

The survey was distributed to 620 prospective participants. 145 responses were received, 88 were disregarded due to;

- 44 are not accountants,
- 6 are practicing outside of South Africa and
- 38 were incomplete.

57 responses were therefore analysed using SPSS IBM software and SmarPLS4. The starting point of data analysis is assessing reliability and validity.

6.1 Validity and reliability

Internal consistency measures consistency between multiple items of the same constructs (Bhattacherjee, 2012). Internal consistency was measured through Cronbach Alpha and found to be above 0.7 for all scales apart from perceived threat of professional obsolescence (PTPO) which was -0.3. After assessment, item 2 of professional obsolescence was removed due to low factor loading, this improved Cronbach Alpha to 0.6. A factor of 0.6 is acceptable (Berger and Hänze, 2015; van Griethuijsen et al., 2015), the scales are therefore reliable. Item 4 of performance expectancy (PE) was dropped due to a factor loading that is less than recommended 0.3 (Bhattacherjee, 2012), refer to table R2. 50% of the constructs showed a Cronbach Alpha score of 0.9, 25% scored 0.8 and 12.25% scored 0.6 and 1.

Average variance extracted (AVE) was used to test convergent validity which assesses at how closely a measure relates to the construct that it purports to measure. AVE was at least 0.5 for all the constructs after the removal of one item in both social influence (SI) and facilitating conditions (FC). The removal was due to the issue of low loadings and high cross-loadings. AVE scores for the balance of the constructs are 0.7 for social influence and behavioural intention (BI); 0.6 for effort expectancy (EE), hedonic motivation (HM), habit (HT), and threat of professional obsolescence. Convergent validity of the instrument is therefore confirmed (Hoehle and Venkatesh, 2015; Kwateng et al., 2019), refer to tables R2 and R5. In Table R5 the items under the 8 constructs are presented as loading together, with factor loadings ranging from 0.6 to 0.9.

6.2 Multicollinearity

Multicollinearity is where there is high correlation amongst the independent variables, if existing it will compromise the reliability of statistical inferences made on the data set (Kim, 2019). Multicollinearity was first tested through examining the correlation of the latent variables. On table R4 (which contains the correlations amongst the constructs) the highest value was 0.78, this is a first indicator that there is no issue of multilinearity. A Variance inflation factor (VIF) test was performed which further confirmed the correlation result (Singh and Matsui, 2017). Table R6 depicts VIF for PE (2.157), EE (2.634), SI (1.404), FC (1.583), HM (2.373), HT (2.492) and PTPO (1.183). These scores are below the maximum of 5 (Kwateng et al., 2019; Palau-Saumell et al., 2019).

6.3 Structural Model

Table R3 depicts the descriptive statistics of the data set. Majority of the variables are presenting as negatively skewed, except gender, age and voluntariness. Distribution for voluntariness, experience and PE is highly leptokurtic with kurtosis of 25.8, 7.2, 5.6, respectively. The skewness and kurtosis figures already suggest that the data is not normally distributed. "Shapiro-Wilk test is the most powerful normality test"(Razali and Wah, 2011, p.21) and was thus applied to test the data for normality. The results show most Sig. values falling below 0.05, which confirms that the data is not normally distributed, see table R7. As per table R7 Sig. values are 0.000 for PE, EE and BI; 0.001 for SI and FC; 0.006, 0.020, 0.028 and 0.005 for HM, HT, PTPO and use respectively. Normal distribution analysis methods were thus eliminated and a more suitable model of analysis was selected - partial least squares (PLS), through the tool SmartPLS. PLS is appropriate for the context of the research since it supports the complexity of the relationships in the model (Hair et al., 2014).

Coefficient of determination, Effect size and predictive relevance

To assess the results of the structural model, we analysed the coefficient of determination (R^2), adjusted R^2, Effect size (f^2) and predictive relevance (Q^2). R^2 is a measurement of how capable the model is to make predictions; R^2 adjusted reduces R^2 to counter the manipulation of adding constructs to the model that are not significant only to improve $R^{2;}$ $f2$ tracks changes in R^2 as a result of removing a construct from the model; Q^2 measures the predictive relevance of the model (Kwateng et al., 2019).

This study employed the “rule of thumb regarding an acceptable R^2,with 0.75, 0.50, 0.25, respectively describing substantial, moderate, or weak levels of predictive accuracy”(Hair et al., 2014, p. 113). With R^2 adjusted of 0.387 and 0.123 for behavioural intention and use behaviour respectively, the model has weak levels of predictive accuracy (see Table R8).

According to Cohen (1988), the effect size of a removed construct is regarded as small, medium and large if it is 0.02, 0.15, and 0.35 respectively. As per Table R9, f^2 is medium to small. When Q^2 value exceeds zero, the path is regarded as having predictive relevance. As per table R10, majority of the paths do not have predictive relevance except BI and U.

Path coefficients for direct relationships were calculated on SmartPLS, the results are shown on table R11. “Path coefficient values are standardized on a range from -1 to +1, with coefficients closer to +1 representing strong positive relationships and coefficients closer to -1 indicating strong negative relationships”(Hair et al., 2014, p.114). A bootstrapping operation was completed using 5000 sample to test the significance of the path coefficients (Hair et al., 2014; Kwateng et al., 2019). With the exception of EE→BI (path coefficient 0.035) and FC→U (path coefficient 0.427) which show a negative relationship, all the unmoderated paths are mostly showing weak positive relationships. At 10% probability of error, bootstrapping highlighted HM (p-value 0.027) and SI (p-value 0.009) as influencers of BI and FC (p-value 0.056) as an influencer of U. Figure 3 graphically shows the p=values of BI→U (0.493), EE→BI (0.422), FC→BI (0.286), HT→BI (0.400), HT→U (0.438), PE→BI (0.269) and PTPO→BI (0.240) which exceed 0.1 and render the relationships insignificant.

Table R1 contains the descriptive statistics for characteristics of the study participants.

Table R1 : Descriptive statistics

Categorical Variable	Category	Frequency	Percentage
Age	35 and below	31	54%
	Above 35	26	46%
Gender	Female	20	35%
	Male	37	65%
Experience	Above 3 years	52	91%
	3 years and below	5	9%
Voluntariness	Voluntary	55	96%
	Nonvoluntary	2	4%

Table R2 depicts the results of testing for Internal consistency through Cronbach Alpha.

Table R2: Validity and reliability of constructs		
Construct	Cronbach alpha	AVE
Performance Expectancy	0,8	0,5
Effort Expectancy	0,9	0,6
Social Influence	0,9	0,7
Facilitating Conditions	0,8	0,5
Hedonic Motivation	0,9	0,6
Habit	0,9	0,6
Perceived Threat of Professional Obsolescence	0,6	0,6
Behavioural intention	1,0	0,7

Table 3 depicts the descriptive statistics of the shape of the data.

Table R3: Descriptive statistics – shape				
Construct	Means	Standard deviation	Skewness	Kurtosis
Performance Expectancy	5,85	1,14	-2,03	5,64
Effort Expectancy	5,28	1,25	-1,24	2,11
Social Influence	4,99	1,46	-0,96	0,66
Facilitating Conditions	4,96	1,27	-1,10	1,78
Hedonic Motivation	5,43	1,12	-0,32	-0,07
Habit	4,63	1,53	-0,53	-0,50
Perceived Threat of Professional Obsolescence	4,84	1,31	-0,67	0,33
Behavioural intention	5,96	1,03	-0,66	-0,77
Use	3,33	0,93	-0,40	-0,83
Age	1,46	0,50	0,18	-2,04
Experience	1,09	0,29	2,99	7,22
Gender	1,65	0,48	-0,64	-1,65
Voluntariness	1,04	0,19	5,19	25,85

Table R4 depicts the correlation of the latent variables.

Table R4: Spearman's rank correlations

	Age	Experience	Gender	Voluntariness	PE	EE	SI	FC	HM	HT	PTPO	BI	U
Age	1,000	-0,159	0,157	0,017	-0,093	-0,119	-0,092	-0,118	-0,046	-0,088	-0,044	-0,072	0,031
Experience	-0,159	1,000	-0,032	,278*	0,173	0,174	0,122	0,192	0,135	0,138	0,038	0,021	-,274*
Gender	0,157	-0,032	1,000	0,140	-0,180	-0,038	-0,128	-0,109	0,139	0,039	0,083	-0,059	0,018
Voluntariness	0,017	,278*	0,140	1,000	0,088	0,119	0,146	0,146	-0,061	-0,020	0,199	0,092	-0,140
PE	-0,093	0,173	-0,180	0,088	1,000	,492**	,405**	,382**	,454**	,485**	-0,022	,497**	-0,047
EE	-0,119	0,174	-0,038	0,119	,492**	1,000	,424**	,555**	,498**	,518**	-,270*	,498**	-0,234
SI	-0,092	0,122	-0,128	0,146	,405**	,424**	1,000	,346**	,266*	,262*	0,072	,528**	-0,199
FC	-0,118	0,192	-0,109	0,146	,382**	,555**	,346**	1,000	,406**	,456**	-0,116	,437**	-,332*
HM	-0,046	0,135	0,139	-0,061	,454**	,498**	,266*	,406**	1,000	,782**	0,022	,515**	-0,195
HT	-0,088	0,138	0,039	-0,020	,485**	,518**	,262*	,456**	,782**	1,000	-0,026	,490**	-0,165
PTPO	-0,044	0,038	0,083	0,199	-0,022	-,270*	0,072	-0,116	0,022	-0,026	1,000	0,086	-0,039
BI	-0,072	0,021	-0,059	0,092	,497**	,498**	,528**	,437**	,515**	,490**	0,086	1,000	-0,128
U	0,031	-,274*	0,018	-0,140	-0,047	-0,234	-0,199	-,332*	-0,195	-0,165	-0,039	-0,128	1,000

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table R5 depicts the factor loadings for assessing convergent validity.

Table R5: Rotated Component Matrix						
	Component					
	1	2	3	4	5	6
PE 1	0,724					
PE 2	0,765					
PE 3	0,582					
EE 1	0,777					
EE 2	0,762					
EE 3	0,721					
EE 4	0,839					
SI 1			0,818			
SI 2			0,884			
SI 3			0,811			
FC 2					0,752	
FC 3					0,756	
FC 4					0,654	
HM 1		0,694				
HM 2		0,808				
HM 3		0,862				
HT 1		0,698				
HT 2		0,895				
HT 3		0,763				
PTPO 1						0,885
PTPO 3						0,666
BI 1				0,866		
BI 2				0,850		
BI 3				0,829		

Table R6 depicts the results of multicollinearity.

Table R6: Collinearity Statistics		
Model	Tolerance	VIF
PE	0,464	2,157
EE	0,380	2,634
SI	0,712	1,404
FC	0,632	1,583
HM	0,421	2,373
HT	0,401	2,492
PTPO	0,845	1,183

Table R7 depicts the results of testing the data for normality.

Table R7: Shapiro-Wilk Tests of Normality			
	Statistic	Df	Sig.
PE	0,808	57	0,000
EE	0,902	57	0,000
SI	0,914	57	0,001
FC	0,917	57	0,001
HM	0,938	57	0,006
HT	0,950	57	0,020
PTPO	0,953	57	0,028
BI	0,862	57	0,000
U	0,937	57	0,005
Age	0,634	57	0,000
Experience	0,319	57	0,000
Gender	0,604	57	0,000
Voluntariness	0,181	57	0,000

Table R8 depicts the results of Coefficient of determination (R^2) and adjusted R^2.

Table R8: Coefficient of determination (R^2) and adjusted R^2		
	R-square	R-square adjusted
BI	0.464	0.387
U	0.170	0.123

Table R9 depicts how R^2 changes because of removing a construct from the model.

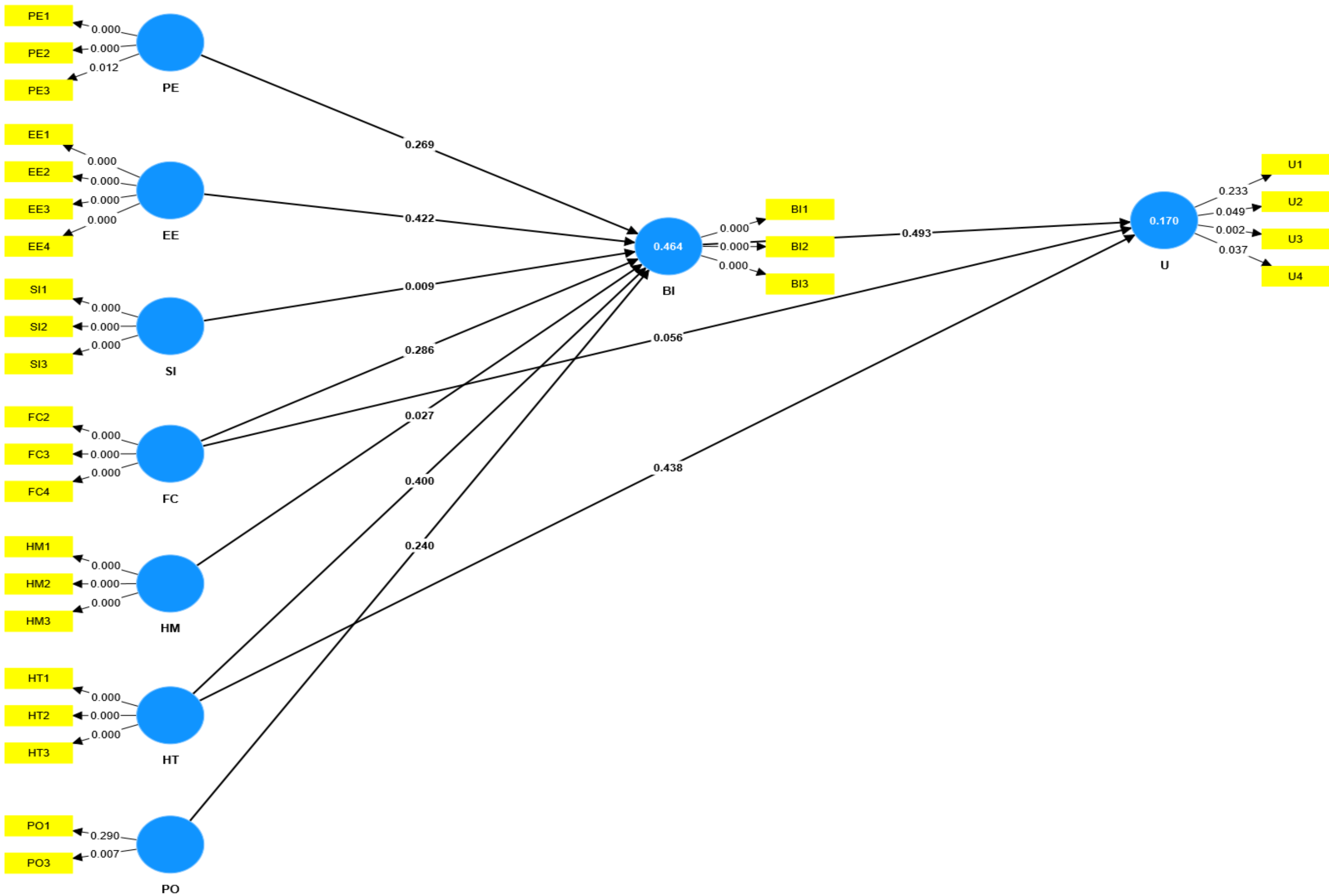
Table R9: Effect size	
	f-square
EE>BI	0.001
FC>BI	0.014
FC>U	0.171
HM>BI	0.086
HT>BI	0.002
HT>U	0.001
PE>BI	0.012
PO>BI	0.015
SI>BI	0.146
BI>U	0.000

Table R10 depicts the results of testing the model for predictive value through Q^2.

Table R10: Predictive relevance	
	Q^2
BI	0.368
EE	0.000
FC	0.000
HM	0.000
HT	0.000
PE	0.000
PO	0.000
SI	0.000
U	0.005

Figure 3: P-values of the structural model.

Results as per partial least squares regression analysis.



6.4 Moderation

As per Table R1 and R3, voluntariness and experience were leptokurtic and highly skewed. The sample is 91% and 96% advanced in experience and work under voluntary conditions respectively. The kurtosis scores for experience and voluntariness are 7.2 and 25.8 respectively. The two moderators were removed from the model as their results could not be reliably extended to the population. 54% of the sample is below the age of 35% while 65% are male. The related kurtosis scores are -2.0 and -1.6 for age and gender respectively. These remaining moderators were tested through running multigroup analysis in SmarPLS.

Age moderation results are contained in table R12. For BI →BU and BI→U the relationships are negative for the younger group and positive for older group, the relationships are however insignificant as evidenced by the p-values that are greater than 0.1. For EE→BI the relationship is positive and significant for the younger, and negative and insignificant for the older group. FC→BI shows a negative insignificant younger group, and a positive significant older group. For FC→U the relationship is negative and significant for the younger group. The HM→BI relationship is significant and stronger for the older group. The HT→BI, HT→U, PE→BI and PTPO→BI relationships are insignificant. SI→BI shows an even split between the young and the old, in both instances the relationships are significant.

Gender moderation results are displayed on table R13. For BI →BU the relationship is negative yet insignificant. For EE →U, HT →BI and PTPO→BI the relationships are negative yet insignificant for both male and female. FC →BI and PE →BI show a negative relationship for males and a stronger relationship for females, though insignificant in both cases. For FC →U the relationship is negative and significant for the female group. HM →BI the relationship is positive and significant in favour of males compared to females. HM →BI is insignificant. For HM→BI the relationship favours females, however the p-value is leaning towards insignificance.

6.4.1 Hypothesis one:

Age and gender will moderate the relationship between performance expectancy and behavioural intention to the extent that the influence will be positive in the case of younger male accountants.

For H1, the moderation of the behavioural intention/performance expectancy relationship is stronger and positive for younger accountants. The moderation is however negative for males. The hypothesis is not supported given all the relationships are not significant.

6.4.2 Hypothesis two:

Age, gender and experience will moderate the relationship between effort expectancy and behavioural intention to the extent that the influence will be positive for older female accountants with limited experience.

For H2, effort expectancy impacts behavioural intention more for younger male accountants, however the relationship is not significant, the hypothesis is not supported.

6.4.3 Hypothesis three:

Age, gender, experience and voluntariness will moderate the relationship between social influence and behavioural intention to the extent that the influence will be positive in the case of older female accountants with limited experience and are subjected to obligatory use.

H3 is not supported, the results show no differences between the younger and older group with a significant impact on males rather than females as hypothesized.

6.4.4 Hypothesis four:

Age and gender will moderate the relationship between facilitating conditions and behavioural intention to the extent that the influence will be positive for older female accountants.

H4 is partially supported in the case of older accountants – with a significant relationship. Though gender difference favoured females, the relationship was insignificant.

6.4.5 Hypothesis five:

Age and experience will moderate the relationship between facilitating conditions and use to the extent that the influence will be positive in the case of older accountants with little experience.

H5 is not supported, facilitating conditions seem to reduce usage in the case of younger females.

6.4.6 Hypothesis six:

Age, gender and experience will moderate the relationship between hedonic motivation and behavioural intention to the extent that the influence will be positive in the case of younger male accountants with little experience.

H6 is partially supported, hedonic motivation influences behavioural intention for males, who are older contrary to the hypothesis.

6.4.7 Hypothesis seven – ten:

Seven: ***Age, gender and experience will moderate the relationship between habit and behavioural intention to the extent that the influence will be positive in the case of older male accountants with advanced experience.***

Eight: ***Age, gender and experience will moderate the relationship between habit and usage to the extent that the influence will be stronger in the case of older male accountants with advanced experience.***

Nine: ***Experience will moderate the relationship between behavioural intention and use to the extent that the influence will be positive for the accountants with less experience.***

Ten: ***Age will moderate the relationship between perceived threat of professional obsolesce and behavioural intention to the extent that the influence will be positive in the case of younger accountants.***

H7, H8, H9 & H10 are not supported due to all the relationships not being significant.

Table R11 depicts the path loading of the structural model.

Table R11: Path coefficients of the structural model					
	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BI -> U	0.004	-0.019	0.218	0.018	0.493
EE -> BI	-0.035	-0.003	0.179	0.198	0.422
FC -> BI	0.113	0.074	0.200	0.564	0.286
FC -> U	-0.427	-0.375	0.268	1.593	0.056*
HM -> BI	0.341	0.297	0.176	1.934	0.027*
HT -> BI	0.051	0.048	0.202	0.253	0.400
HT -> U	0.032	0.034	0.208	0.156	0.438
PE -> BI	0.117	0.138	0.190	0.614	0.269
PTPO -> BI	0.101	0.081	0.143	0.706	0.240
SI -> BI	0.333	0.382	0.141	2.363	0.009*

*significant

Table R12 depicts the results bootstrapping computed on SmartPLS to test the data for age moderation.

Table R12: Age moderation multigroup analysis

	Original		Mean		STDEV		t value		p value	
	35 & below	Above 35	35 & below	Above 35	35 & below	Above 35	35 & below	Above 35	35 & below	Above 35
BI -> U	-0.043	0.088	-0.026	0.001	0.253	0.413	0.170	0.214	0.432	0.415
EE -> BI	0.245	-0.407	0.212	-0.255	0.190	0.469	1.285	0.868	0.099	0.193
FC -> BI	-0.266	0.407	-0.204	0.292	0.331	0.288	0.803	1.415	0.211	0.079
FC -> U	-0.346	0.118	-0.376	-0.071	0.235	0.524	1.473	0.225	0.070	0.411
HM -> BI	0.149	0.802	0.084	0.636	0.257	0.425	0.582	1.889	0.280	0.029
HT -> BI	0.133	-0.380	0.069	-0.252	0.247	0.426	0.539	0.890	0.295	0.187
HT -> U	-0.227	0.338	-0.217	0.156	0.285	0.421	0.794	0.803	0.214	0.211
PE -> BI	0.214	0.043	0.286	0.056	0.245	0.356	0.874	0.120	0.191	0.452
PTPO -> BI	0.044	0.083	0.031	0.037	0.202	0.208	0.217	0.398	0.414	0.345
SI -> BI	0.535	0.547	0.538	0.512	0.235	0.287	2.275	1.908	0.011	0.028

Table R13 depicts the results bootstrapping computed on SmartPLS to test the data for gender moderation.

Table R13: Gender moderation multigroup analysis										
	Original (Female)	Original (Male)	Mean (Female)	Mean (Male)	STDEV (Female)	STDEV (Male)	t value (Female)	t value (Male)	p value (Female)	p value (Male)
BI -> U	-0.089	-0.129	-0.060	-0.102	0.377	0.317	0.235	0.405	0.407	0.343
EE -> BI	0.097	0.148	0.170	0.082	0.421	0.241	0.232	0.613	0.408	0.270
FC -> BI	0.220	-0.025	0.129	0.008	0.392	0.279	0.562	0.090	0.287	0.464
FC -> U	-0.560	-0.511	-0.483	-0.237	0.312	0.494	1.795	1.035	0.036	0.150
HM -> BI	0.109	0.341	0.062	0.287	0.558	0.265	0.195	1.288	0.423	0.099
HT -> BI	-0.136	0.229	-0.032	0.174	0.656	0.288	0.208	0.794	0.418	0.214
HT -> U	0.159	0.115	0.033	0.041	0.437	0.273	0.364	0.420	0.358	0.337
PE -> BI	0.270	-0.130	0.294	-0.040	0.497	0.247	0.544	0.525	0.293	0.300
PTPO -> BI	0.109	0.166	0.074	0.134	0.460	0.179	0.237	0.931	0.407	0.176
SI -> BI	0.445	0.397	0.445	0.441	0.473	0.179	0.940	2.212	0.174	0.013

7 DISCUSSION

This research has tested and confirmed partial applicability of the UTAUT2 model in understanding adoption and use of BDA tools. Age and gender are the only moderators which could be reliably tested. Two hypotheses (H4 and H6) were partially supported. Access to end-user support and current information boost intention to use BDA tools (Wibowo et al., 2022). Managers will have to show commitment to adoption of BDA tools by investing in end-user support and providing current information through training and other similar means. Professional bodies should support the adoption drive by also providing regular updates as done for other technical skills such as tax. The BDA tools selected by business should be designed in a manner that makes the tools fun to use. The gratification of using the tools will boost adoption irrespective of whether accountants find the tool useful (Prakash and Das, 2020).

8 CONTRIBUTION OF THE STUDY

This research has added to the limited South African literature on the subject of adoption of BDA tools by accountants. The study has highlighted the importance of providing end-user support and availing tools that are pleasurable to use.

Limitations and future research

Since experience and voluntariness were dropped in this study, there is an opportunity to study the two moderators in future research using a more diverse sample. There was no statistically significant evidence to support majority of the UTAUT2 relationships, other models thus need to be explored to get deeper insights into the adoption of BDA tools by accountants practicing in SA. The response rate was low at 16% (9% usable responses) which limits the generalisability of the study(Lee and Chang, 2020).

9 CONCLUSION

In this study UTAUT2 was applied in a new context. Main findings are that facilitating conditions moderated by age and hedonic motivation moderated by age and gender are drivers of behavioural intention. Other models need to be explored to understand adoption of BDA tool by accountants in SA.

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11 APPENDIX

11.1 Survey instrument

1. Are you an accountant?
    - Yes
    - No

2. Are you practicing in South Africa?
    - Yes
    - No

3. Age group
    - 35 and below
    - Above 35

4. Experience
    - 3 years and below
    - Above 3 years

5. Gender
    - Female
    - Male

6. Voluntariness
    - Voluntary
    - Nonvoluntary

Unless directed otherwise, the following questions must be answered by choosing one of the below responses:

Strongly disagree	**Disagree**	**Somewhat disagree**	**Neither disagree nor agree**	**Somewhat agree**	**Agree**	**Strongly agree**

Seven-point Likert scales

Behavioural Intention (BI)	
Performance Expectancy (PE)	PE1. I find big data analytics tools useful in my job
	PE2. Using big data analytics tools enables me to accomplish tasks quicker
	PE3. Using mobile Internet increases my productivity
	PE4. If I use big data analytics tools, I will increase my chances of getting a raise
Effort Expectancy (EE)	EE1. Learning how to use big data analytics tools is easy for me
	EE2. My interaction with big data analytics tools is clear and understandable
	EE3. I find big data analytics tools easy to use
	EE4. It is easy for me to become skilful at using big data analytics tools
Social Influence (SI)	SI1. People who are important to me think that I should use big data analytics tools
	SI2. People who influence my behaviour think that I should use big data analytics tools
	SI3. People whose opinions that I value prefer that I use big data analytics tools
	SI4. Senior management of the business require me to use big data analytics tools
Facilitating Conditions (FC)	FC1. I have the resources necessary to use big data analytics tools
	FC2. I have the knowledge necessary to use big data analytics tools
	FC3. The big data analytics tool is compatible with other tools I use
	FC4. A specific person (or group) is available for assistance with big data analytics tool difficulties
Hedonic Motivation (HM)	HM1. Using the big data analytics tool is fun
	HM2. Using the big data analytics tool is enjoyable
	HM3. Using the big data analytics tool is very entertaining
Habit (HT)	HT 1. The use of the big data analytics tool has become a habit for me
	HT2. I am addicted to using the big data analytics tool
	HT3. I must use the big data analytics tool
Perceived threat of professional obsolescence (PO)	PO1. I feel like some of my skills as an accountant are becoming obsolete because of big data analytics tools
	PO2. I do not feel as if my current job skills as an accountant are becoming outdated
	PO3. There are lots of changes to this job that relate to big data analytics tools that I wish I knew more about so that I could do better

Behavioural Intention (BI)	BI1. I intend to use a big data analytics tool in the 12 months
	BI2. I predict I would use the big data analytics tool in the next 12 months
	BI3. I plan to use the big data analytics tool in the next 12 months

Please select your frequency of use of the tools in line with five options below:

Never	**Rarely**	**Sometimes**	**Frequently**	**Many times a day**

Five-point Likert scales

Use
I. Power BI
II. Qlik Sense
III. SAP Business Objects BI Suite
IV. Tableau Desktop

11.2 Invitation to participate

Dear Sir / Madam

My name is Bongiwe Sithole. I am a Masters student in Information Systems at the University of the Witwatersrand, Johannesburg. My supervisor is Neetu Ramsaroop. I am conducting a research study about adoptions of big data analytics tools. The study title is Adoption of Big Data analytics tools by accountants practicing in South Africa.

I am inviting you to take part in a questionnaire. If you decide to take part, your participation in this research study will last about 20 minutes. The questionnaire is online.

During the research activity, I will need to ask for some personal information about you, including age and gender.

The questionnaire will be confidential and anonymous. When I share the results of the research study in the research report, I will not include your name or anything else that could identify you.

If you decide to take part in the research study, it should be because you want to volunteer. You do not have to take part. You can stop being in the study at any time. You do not have to answer any questions if you do not want to. You will not get any direct benefits if you choose to join the research study. You will not lose any services, benefits or rights you would normally have if you decide not to join. Taking part in the research study will not cost you anything. You will not be paid for being in this research study.

The risks for this research study are no more than what happens in everyday life.

This research study will be written up as a research report. The report will be available on the university library website. If you would like to receive a summary of this report, I will be happy to send it to you.

If you have any questions during or afterwards about this research study, feel free to contact me or my supervisor on the details listed below. If you have any concerns or complaints about the ethical procedures of this research study, you are welcome to contact the University Human

Research Ethics Committee (Non-Medical), telephone +27(0) 11 717 1408, email hrecnon-medical@wits.ac.za.

Yours sincerely,
Bongiwe

Researcher:
Bongiwe Sithole, 382195@students.wits.ac.za

Supervisor:
Neetu Ramsaroop, neetu.ramsaroop@wits.ac.za

11.3 Ethical clearance

UNIVERSITY OF THE WITWATERSRAND, JOHANNESBURG

SCHOOL OF BUSINESS SCIENCES ETHICS COMMITTEE
CONSTITUTED UNDER THE UNIVERSITY HUMAN RESEARCH ETHICS COMMITTEE (NON-MEDICAL)

CLEARANCE CERTIFICATE	**PROTOCOL NUMBER: CBUSE2059**
PROJECT TITLE	Adoption of Big Data analytics tools by accountants practicing in South Africa.
INVESTIGATOR	Bongiwe Sithole
SCHOOL/DEPARTMENT OF INVESTIGATOR	School of Business Sciences
DATE CONSIDERED	18 October 2022
DECISION OF THE COMMITTEE	Approved Unconditionally
RISK LEVEL	Minimal Risk
EXPIRY DATE	31 December 2025

ISSUE DATE OF CERTIFICATE 03 November 2022 **CHAIRPERSON** ______________
(Neetu Ramsaroop)

cc: Supervisor: Dr Neetu Ramsaroop

DECLARATION OF INVESTIGATOR

To be completed in duplicate and **ONE COPY** returned to the Chairperson of the School/Department ethics committee.

I fully understand the conditions under which I am are authorized to carry out the abovementioned research and I guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I/we undertake to resubmit the protocol to the Committee.

______________________ **Signature** **Date** _____/_____/_____

|PLEASE QUOTE THE PROTOCOL NUMBER ON ALL ENQUIRIES